

## **How wealth of nations interact with aid and peace: A time and country variant analysis**

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**Abstract:** By using panel VAR model and directed acyclic graphs (DAGs), we explore the dynamic interdependences among aid, development, and conflict. We construct a worldwide panel dataset of 79 countries over the period 1995-2010. Although foreign aid is sensitively responsive to the conflict or development shock, its effects on reducing conflict and improving development are largely relied on the wealth level and conflict proneness of the recipient country. We find that foreign aid only mitigates conflict in middle income developing countries, and enhances the development of the poor and conflict-prone countries.

## **1. Introduction and Literature Review**

As a perpetual topic for human beings, its connotation should be enriched by introducing the consideration of conflicts and foreign assistance in order to match the global development trend. Scholars generally agree that foreign assistance, development and conflict have a high correlation among each other but fail to reach a unanimous consensus on the underlying causalities. The ineffectiveness of foreign aid, conflict reduction strategies and poverty eradication strategies can largely be attributed to this failed understanding of the causal relationships and consequences among these variables. As regards the empirical study side, there have been numerous studies concerning foreign aid, conflict and development, but unfortunately, none of them consider all of these variables together in one model.

On one hand, conflicts ought to be central in the study of development for developing countries, especially for those poorest countries. In any year over the last decade, 25-30 countries had an internal armed conflict. Collier (2008) calculated that economic growth is reduced by 2.3% per year on average due to conflict. World Bank expressed that conflict is a global issue instead of special case, claiming that state fragility and conflict exact terrible tolls on over 600 million

people across the world (World Development Report, 2011). We also find a great coincidence that almost 80% of conflict-affected nations are the poorest countries. Since conflict shows all kinds of negative impacts on development, it is portrayed as “development in reverse” (Collier, 2004) or “stymieing development and macroeconomic growth” (Stewart et al., 2000), which described conflict as the opposite side of development.

Conflicts are not distributed randomly across the world. Collier used the term “Conflict Trap” because he found conflicts disproportionally occur in a group of about 50 countries, or in ‘the bottom billion’ population of the world (Collier; 2003, 2007). United Nations also recognized this phenomenon and defined 29 conflict-affected countries. The assumption of conflict trap is that conflict deteriorates the structural factors, such as poverty, governance, which tend to facilitate conflict in the future. In other words, the chief legacy of a conflict is another conflict. Compared to the “development in reverse” statement, “Conflict Trap” presents a much stronger proposition, implying that the conflict-affected countries cannot get out of the trap without foreign assistance.

The correlates of conflict are by now well-discussed. Humphreys (2003), Blattman and Miguel (2010) have made comprehensive literature review on the “causes”<sup>1</sup> and effects of conflicts. The correlation between low GDP per capita and higher propensities for conflicts is one of the most robust empirical relationships in the literature. Collier and Hoeffler (1998) argue that increasing income per capita is expected to decrease the probability of conflict when economic alternatives for potential rebels evolve and improve. An alternative explanation of GDP per capita is proposed by Fearon and Laitin (2003). Their point of view is that GDP per capita is a proxy for

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<sup>1</sup> In many cases it is still not clear whether the correlates actually cause conflict or are merely symptoms of deeper problems.

the state's overall financial, administrative, police and military capabilities. The latter argument may over-explain the implications of GDP per capita. Nevertheless, Fearon and Laitin also found that per capita income is a robust predictor of civil war. Another correlate of conflict is infant mortality rates. Esty et al. (1998) reported very strong effects of infant mortality on state failure and conflict. Urdal (2005) found high infant mortality rates to be strongly associated with an increased risk of armed conflict onset. Trade is proposed as a potential correlate but showed a less consistent relation to conflict (Blattman and Miguel, 2010). It is noticeable that conflict and development have dual effects. Besides the costs of conflict on development, leading academics (see Sachs, 2005; for example) have also advocated poverty reduction and socio-economic development in order to reduce violent conflict.

Apart from development index, several institutional and distributional factors are also in the debate, including state fragility, democracy, income/ ethnical inequality. Comparing state fragility and democracy, the former shows a closer association with conflict. Hegre (2002) tested and confirmed the theory that both solid democratic and harsh autocratic regimes are associated with less civil war than those that are considered to be at an intermediate level of democracy. Collier and Hoeffler (1998; 2004) argued that democracy is not statistically significant predictors of conflict risk conditional on other factors. They are also skeptic about the role of ethnic fractionalization and income inequality. Their points are supported by Fearon and Laitin (2003) stating that ethnic diversity, inequality, discrimination, and democratic institutions are weakly correlated with the onset of armed conflicts.

Foreign aid is the last well-discussed correlate of conflicts. Ree and Nillesn (2009) explained the logic that aid donated to developing countries will help those countries to improve their economic conditions, which are related to conflict. That is to say, foreign assistance is not the

direct cause of conflicts reduction, but will directly cause the (economic) development. So, a new question arises: Does foreign aid really help the developing countries? Sachs (2005) argued that 0.7% of the GNP of rich countries would be enough to eliminate hunger and endemic disease if devoted to the poor of the world.<sup>2</sup> According to Sachs, with appropriate allocation of the increased aid resources, extreme global poverty of under a dollar per day could be eliminated by 2025. On the contrast, pessimistic economists believe that reformation and execution of aid is futile and corrupted. For example, Easterly (2006) stated that the chief reason for lack of development progress in modern times is not the lack of aid; instead, he argued it is non-democratic governance and corrupt politics and administration in countries receiving this aid. Through empirical analysis, Burnside and Dollar (2000) discovered that aid has a positive impact on growth in developing countries with good fiscal, monetary and trade policies. While in the presence of poor policies, aid has no positive effect on growth. Furthermore, Svensson (2000) and Easterly et al. (2004) failed to discover any evidence that foreign aid brings development.

The remainder of this paper is organized as follows. In Section 2 we discuss the data set, variable selection and some important stylized facts, and in Section 3 we discuss the estimation strategy. Section 4 presents our results. Section 5 concludes.

## **2. Data Description**

Data is collected from 79 developing countries over 16 years, from 1995 to 2010. Due to lack of statistical data, Small Island developing countries and developing countries whose populations

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<sup>2</sup> The world's richest countries provided just 0.33% of their GNP in official development assistance (ODA) in 2005. And the ODA has been declined in the recent years due to financial crisis.

are smaller than 500,000 are excluded from the sample<sup>3</sup>. The 79-country sample is quite representative for the continental developing countries.

Appropriately cherry-picking conflict variable for the empirical exercise is important. Although we followed previous researchers using The Uppsala University Conflict Data Program (UCDP) database (Gleditsch et al., 2002), we choose different measures of conflicts. UCDP defines armed conflict as “a contested incompatibility that concerns government or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths.” Every conflict is recorded by UCDP. UCDP has two measurements of conflicts based on its definition of conflict: UCDP firstly collects the amount of battle-related deaths for each country-year; then a secondary measurement is created given the amount of battle-related deaths, which is called “conflict intensity”. Conflict intensity is measured by grades on the scale of battle-related deaths, with higher grade indicating more intensive conflict events<sup>4</sup>. So far, the discrete measurement of conflict has been popular in the previous studies because of its fitness for econometrician models for categorical dependent variable (Ree and Nillesn 2009; Collier and Hoeffler 2002; Miguel, Satyanath, and Sergenti 2004; Fearon and Laitin 2003). For instance, one can set up a threshold<sup>5</sup>. If the amount of battle-related deaths passes the threshold, then it is regarded as “Conflict Onset”, while conflict fatality below the threshold is regarded as “Conflict Ending”. In our empirical analysis, we choose to use conflict fatality, which is the real amount of battle-related deaths, to indicate the degree of conflicts by the following reasons. Firstly, the judgment of proper

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<sup>3</sup> According to World Bank, there are totally 152 developing countries in the world. We dropped 46 Small Island developing countries and 5 developing countries that have populations no greater than 500,000.

<sup>4</sup> Conflict intensity is measured in the following way. “0”: battle-related death number is lower than 25 in a given year; “1”: between 25 and 999 battle-related deaths in a given year; “2”: at least 1,000 battle-related deaths in a given year.

<sup>5</sup> Lower threshold is battle-related deaths > 25; higher threshold could be battle-related deaths > 1,000.

threshold level is completely subjective. Ree and Nillesn (2009) raised concerns that the dynamic analysis using either the Probit Model or Linear Probability Model in the previous literature is heavily depended on the definitions of conflict onset and duration. Thus, their results might be changed if the threshold of conflict onset/ duration is changed. Secondly, when transforming conflict fatality into binary states of conflict, information on volatility of battle-related deaths is missed. For instance, if a country has its conflict fatality dropped from 1000 to 100 but still higher than the threshold, then the state of conflict intensity remains the same despite of the dramatic decline of battle-related deaths. Therefore, we use the amount of conflict fatality, instead of discrete measurements, as the main variable, because it provides an objective, information preservation, and policy-maker friendly way to analyze conflict-related issues. In addition, it is worth mentioning that conflict fatality, which only concerns direct deaths in the conflicts, does not include all war-related deaths (Lacina and Gleditsch, 2005). As a result, conflict fatality is better regarded as an empirical measure of the conflicts size, rather than the total exact loss of conflicts.

As for the data source for foreign aid, OECD Development Assistance Committee (DAC) solely provides the international aid data. Yearly data for each aid receiving country was recorded at constant US million dollars. The foreign aid data reflects the combination of loans, grants and technical co-operation to developing countries. Grants, loans and credits for military purposes are excluded. Previous studies (Collier and Hoeffler, 2002; Ree and Nillesen, 2009; Nielsen et al., 2011) usually employ  $\frac{Aid}{GDP}$  (aid-to-GDP ratio) as the variable, which in fact describes foreign aid as the share of GDP. Yet, ratio variable of aid ignores the population effects and absolute aid changes in the long run (Juselius *et al.*, 2013; Lof *et al.*, 2015). Following their suggestions, we choose aid per capita as the variable to avoid the limitedness of aid-to-GDP ratio.

According to OECD DAC dataset, the official development assistance (ODA) indicates loans have interest rates no greater than 25%.

Other primary variables of interest are the following. GDP per capita is frequently used as an indicator for wealth level. We collected PPP (purchasing power parity) converted GDP per capita data from the Penn World Table (Version 7.1). The variable capturing the non-income development is infant mortality rate. We use the World Bank's measure of the probability per 1,000 that a newborn baby will die before reaching age five, if subject to current age-specific mortality rates. Infant mortality rate is also often regarded as a proxy for poverty. We also consider an index of country stability from the Center for Systemic Peace, because a country's stability is closely associated with its state capacity to manage conflict and sustaining progressive development. The index is called state fragility index (SFI), which has a 25-point fragility scale: ranging from 0 "no fragility" to 25 "extreme fragility". SFI estimates every country on both effectiveness and legitimacy in four performance dimensions: Security, Political, Economic, and Social. In order to capture the effects of hunger, we collected the food inadequacy (FI) rate from FAO. FI measures the percentage of the population that is at risk of not covering the food requirements associated with normal physical activity.

To breakdown the sample by income levels, we followed World Bank and divided all sampled developing countries by \$4,000 and \$12,500. Thus, 47 countries having GDP per capita lower than \$4,000 are grouped as low-income developing countries; 30 countries having GDP per capita between \$4,000 and \$12,500 are classified as middle-income developing countries. Another way to explore the sample in depth is to subgroup the countries by their exposure to conflicts. According to United Nations, 29 countries out of the sample are labeled as conflict-prone countries. It is noticeable that there are 16 middle-income countries in the conflict-prone



group, accounting for more than a half of the conflict-prone countries. Table 1 shows some summary statistics for each variable across all sample groups.

**Table 1 Summary statistics across all groups in the sample**

Variables	Overall sample		Low-income group		Middle-income group		Conflict-prone group	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Conflict Fatality</b>	262	872	363	1,060	118	447	690	1,331
<b>GDP per capita</b>	3,688	3,300	1,514	996	6,805	2,665	2,239	2,173
<b>Infant Mortality</b>	79	58	110	52	36	35	104	61
<b>SFI</b>	13	5	16	4	10	5	17	5
<b>FI</b>	29	18	37	17	17	13	40	19
<b>Foreign Aid</b>	51	63	55	62	43	66	43	68

Column (1) and (2) in Table 1 present the averages and standard deviations of the primary variables of the overall sample. A typical developing country has \$3,688 GDP per capita per year, receives \$65 aid per year, with 79 children out of 1,000 could not reach the age of 5, as well as 262 people died in conflicts per year. The comparison across income groups shown in column (3) – (4) reveals that, the low-income developing countries are fallen behind the middle income developing countries in every socio-economic index. The average of middle-income group's GDP per capita is 4.5 times greater than that of low-income group, and the comparison ratio for

infant mortality is 0.33, the FI ratio is 0.46, and the conflict fatality ratio is 0.33. However, people living in the low-income countries only receive 28% more foreign aids than those living in the middle-income developing countries. Column (7) and (8) show the summary statistics for the conflict-prone group, as expected, the average amount of conflict fatality is much higher than any other groups. We also observe that all socio-economic index excluding GDP per capita in the conflict-prone group are deteriorated than the low-income group, despite the conflict-prone group is constituted by more middle-income countries. It also shows that conflict-prone countries receive less foreign aid than any other groups. We could reach three conclusions from Table 1, as they have been already discussed: firstly, income level of a developing country is closely related to its non-income development level; secondly, there is large room for the distribution of foreign aid to be improved by the levels of wealth and conflict exposure; thirdly, compared the costs on GDP per capita resulted from conflicts, the destructions on non-income development are much more severer and fateful.

## **2.1 Stylized facts**

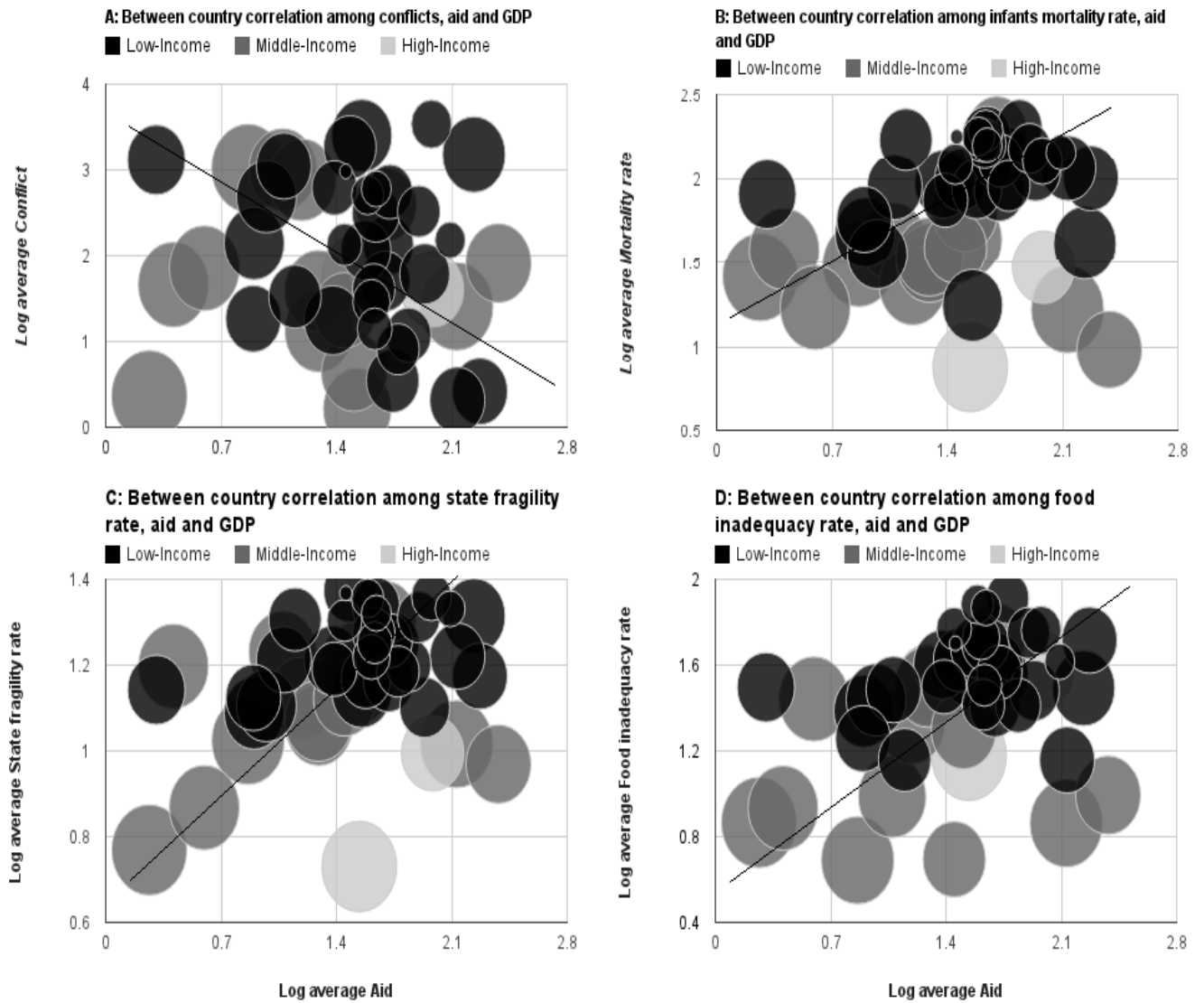
In order to demonstrate the basic relationships among these variables, we employ 3-dimensional bubble charts, which allow us to present 3 variables simultaneously, to provide a more visualized look at some key trends of our variables. We at first average these variables over the time period, then made log transformation on the time averaged variables. As Fig.1 shows, each bubble represents a developing country in the sample. The bubble size indicates the level of GDP per capita, that wealthier country has larger bubble. To classify different income groups, we associate 3 contrastive colors with the income levels.

Fig. 1A reveals the cross country correlations among conflict fatality, aid and GDP per capita. The correlation between conflict and aid seems unclear. However, if we exclude two outliers, Iraq and Afghanistan, in the right-top areas, we find a trend that foreign aid and conflicts are negatively related, especially for low-income group. This observation reinforces our findings from Table 1 that, foreign aid seems flow around the conflict-affected countries.

Shown as Fig. 1B, it is evident that countries with higher mortality rates receive more foreign aid. The exceptions located at the right-bottom corner are Georgia, Lebanon, and Bosnia and Herzegovina, which are hot spots in terms of geopolitical interests and therefore receives substantial amount of aid. Another exception country on the left-top corner is Iran that has high infant mortality rate but is unable to receive international assistance during our sample period.

Fig. 1C clearly shows a trend that more fragile countries receive more aid. The two outliers on the left-top area are Iran and India. Similarly, we find that countries with high food inadequacy rates tend to receive more foreign aid (Fig. 1D). The exception on the left-top corner is Iran; while the other two exceptions located at the right-bottom corner are Lebanon, and Bosnia and Herzegovina.

Although Fig. 1 provides some information on the correlations among the variables of interest in the paper, it is not enough to further get any conclusion on contemporaneous or dynamics causalities. Yet, the correlation analysis is a good start. Given the evident trends shown in the panels in Fig. 1, we expect that these variables play important roles in analyzing the causes and effects among conflicts, development and foreign aid.



**Fig.1.** Cross country correlations among conflict, aid and GDP (Panel A), infants mortality, aid and GDP (Panel B), state fragility rate, aid and GDP (Panel C), food inadequacy, aid and GDP (Panel D).

### 3. Empirical methods

We use a panel vector auto-regression (panel VAR) to investigate the dynamic interdependence among conflict, development and foreign aid. Their contemporaneous (instantaneous) causal directions are explored using methods from machine learning. The result is a directed acyclic graph (DAG) summary of the relationships among innovations from the panel VAR.

The primary econometric model takes the following unrestricted reduced form (Hsiao, 2003):

$$X_{it} = \Gamma_1 X_{i,t-1} + \Gamma_2 X_{i,t-2} + \dots + \Gamma_p X_{i,t-p} + \mu_i + e_{it} \quad (1)$$

where  $X_{it}$  is a six-variable vector  $\{Conflict, GDP, Mort, SFI, FI, Aid\}$ ;  $\Gamma_1, \Gamma_2 \dots \Gamma_p$  indicate the lag operator, where the optimal lag length  $p$  is determined by Schwarz's information criterion (SBC);<sup>6</sup>  $\mu_i$  is a vector of unobserved fixed effects, representing country-specific characteristics in our model;  $e_{it}$  is a vector of idiosyncratic errors.

Panel VAR model has been widely used in applied macroeconomics. As a combination of the time-series VAR approach and panel data estimation techniques, the panel VAR has several advantages in analyzing the dynamic relationships among variables in the system. For instance, as Sambanis (2002) mentioned, endogeneity is one of the major problems in conflict-related research. Previously researchers attempted to overcome endogeneity by adding lagged variables in the structural model, which has underlying assumption that left-hand-side variable is caused by the right-hand-side variables. Yet, the presumed direction of causality in a structural model remains contested (Pearl, 2009). Miguel *et al.* (2004) dealt with endogeneity problems by employing rainfall as the instrumental variable (IV) to study conflicts in Sub-Saharan Africa. In

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<sup>6</sup> The optimal lag length  $p=3$ . The detailed SBC calculation is provided in the appendix.

our study, we use the lagged variables as IV and estimate the coefficients by system generalized method of moments (GMM). Panel VAR simultaneously models all the variables in the system as endogenous. Moreover, the dynamic relationships among the variables are captured by orthogonalized impulse response functions (IRFs), which is a data-driven tool derived from panel VAR model. IRFs describe the dynamic response of one variable to a one standard deviation shock in another variable, while holding the other variables constant.

As it is well known that, the variables in the panel VAR model ought to be stationary. We employed the second-generation panel unit root test to investigate stationarity. Compared with the first-generation tests, the second-generation tests relax the assumption of cross-sectional independence across different panel units. In fact, we argue that cross-sectional dependence exists in this empirical study due to spatial dependence, which is a result of globalization. Furthermore, we made a test for the presence of cross-sectional dependence in panel data, which is developed by Hoyos and Sarafidis (2006). This test performs well in panel data that is characterized by large  $N$  (cross section units) and small  $T$  (time periods). And the test results reject the null hypothesis of cross-sectional independence. We then could implement the second-generation panel unit root test. Pesaran (2007) proposed the cross-sectional augmented Dickey-Fuller (CADF) test, with the null hypothesis of the presence of unit root. The CADF test combined the classical augmented Dickey-Fuller with the approximately lagged cross-sectional mean and its first difference in order to capture the cross-sectional dependence. The results of CADF test are reported in Table 2. For variables in level, we find that the null hypothesis cannot be rejected for all variables except for FI; for variables in first difference, the results show that the null hypothesis could be rejected at acceptable level of significance. Therefore, we conclude from Table 2 that, the variables are non-stationary in level but stationary in first difference.

**Table 2 CADF panel unit root test result**

<b>Variables</b>	<b>Value</b>	<b>P-Value</b>
<b>Conflict</b>	16.67	1.00
<b>Mort</b>	7.22	1.00
<b>GDP</b>	-0.922	0.18
<b>SFI</b>	2.99	0.98
<b>FI</b>	-2.23	0.01
<b>Aid</b>	1.86	0.97
<b>Δ Conflict</b>	-4.44	0.01
<b>Δ Mort</b>	-2.05	0.1
<b>Δ GDP</b>	-2.17	0.08
<b>Δ SFI</b>	-3.36	0.01
<b>Δ FI</b>	-2.52	0.01
<b>Δ Aid</b>	-3.49	0.01

However, it has been noted that the standard first-differencing procedure results in biased coefficients while eliminating fixed effects in Eq. (1). Blundell and Bond (1998) showed that the first-differenced estimates tend to be overestimated, since fixed effects are correlated with the explanatory variables due to the dynamic panel data setting. An alternative to the first-differencing procedure is the following orthogonal deviations (Arellano and Bover, 1995):

$$X_{it}^* = \delta_t \left[ X_{it} - \frac{1}{T-t} (X_{i,t+1} + \dots + X_{iT}) \right], \quad t = 1, \dots, T-1, \quad (2)$$

and

$$e_{it}^* = \delta_t \left[ e_{it} - \frac{1}{T-t} (e_{i,t+1} + \dots + e_{iT}) \right], \quad t = 1, \dots, T-1, \quad (3)$$

where  $\delta_t = \sqrt{(T-t)/(T-t+1)}$ . That is, variables in each of the first (T-1) periods are transformed into deviations from their forward means. The weighting  $\delta_t$  ensures equalized variance and preserves orthogonality in the transformed model. The final panel VAR model is then:

$$X_{it}^* = \Gamma_1 X_{i,t-1}^* + \Gamma_2 X_{i,t-2}^* + \dots + \Gamma_p X_{i,t-p}^* + e_{it}^* \quad (4)$$

Our objective is to investigate the dynamic interactions among variables, that is, how one variable of interest reacts to a one-time shock in another variable, while holding all other shocks constant. The approach we applied to orthogonalize shocks is the Cholesky Decomposition, which places some restrictions on variables ordering. It requires variables that come earlier in the ordering should be weakly exogenous with respect to the variables that appear later. For instance, if variable A is listed earlier than variable B, then A would affect B contemporaneously, but not vice versa. However, variables' lagged impacts are not restricted by Cholesky Decomposition.

Often researchers rely on previous literature or economic theory to identify the contemporaneous causal relationships. Since the literature in the area of conflict and development is not well developed, and the opinions are sometimes conflicting, we choose to follow Bessler and Yang (2006) to identify the VAR ordering. The tool we use is called DAGs, which reveal qualitative causal directions through the directed graphs analysis of the covariance matrix of  $e_{it}^*$  (Pearl, 2009). DAGs could be interpreted as nonparametric structural equation models (NPSEM), since they have no assumption about the functional form of the causal effects



or distribution of the variables (Elwert, 2013). In a DAG, directed arrows are used to represent contemporaneous causal flows. If variables are not connected by arrows, then it implies that there is no direct contemporaneous causal effect. As shown in the appendix, our data is non-Gaussian. Thus, the LiNGAM (Linear, Non-Gaussian, Acyclic causal Models) algorithm developed by Shimizu et al. (2006) is applied here to obtain DAGs. LiNGAM algorithm is based on independent component analysis (ICA), which is only feasible for non-Gaussian data. Once we find the contemporaneous causal order among variables, we are able to compute IRFs.

## **4. Results**

### **4.1 Contemporaneous Relationships**

As explained in the above section, DAG recovers the exogeneity for each variable in order to guide the Cholesky Decomposition in IRF computation. At the same time, DAG also reveals the contemporaneous causal directions among the variables. Although the major influences of foreign aid and other variables often take effect in a time lag, it is helpful to understand their contemporaneous or instantaneous interactions.

Fig. 2 demonstrates the contemporaneous causal directions of the overall sample. It shows that foreign aid has no correlation with the others in the contemporary period. We also observe that GDP per capita and conflict fatality are the consequences, while infant mortality, SFI and FI are the causes in the contemporary period. This finding is repeated by the other DAG causality charts of other subgroups, which are placed in the appendix to save space.

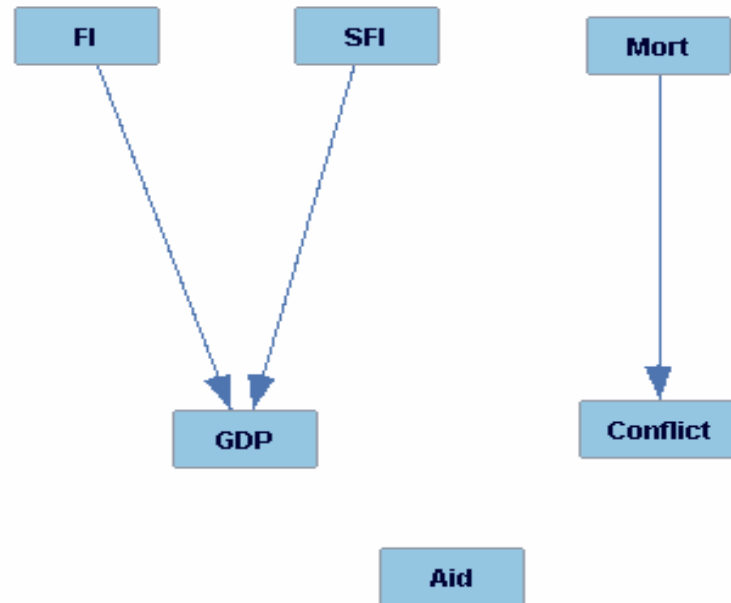


Fig. 2. DAG contemporaneous causality chart for the overall sample

#### 4.2 Dynamic Relationships (Aid and Conflicts)

First of all, it is of great interest to investigate the effects of foreign aid on reducing conflict. Fig.3 shows the dynamic response of conflict fatality to a foreign aid shock. The different panels in this figure provide IRFs based on different sample groups. Panel A of Fig.3 depicts that a positive standard deviation shock to foreign aid per capita (which corresponds to a \$3 increase of aid per capita with respect to its baseline) surprisingly leads to an escalation of conflict for all sampled developing countries, although the climbing trend of conflict is not statistically significant. The next two panels in Fig.3 show similar IRFs for the conflict-prone group and the low-income group. The impact of a shock to foreign aid on conflict becomes significant in the first year for the low-income group, as it suggests in Panel C. However, the effect of foreign aid shock on conflict fatality changes drastically for the middle-income group, as it is shown in Panel D. Comparing panels B, C and D, it appears that aid will only be able to reduce conflict in

countries which have better economic infrastructure; and for poorer or conflict prone economies an aid shock will even exacerbate conflict.

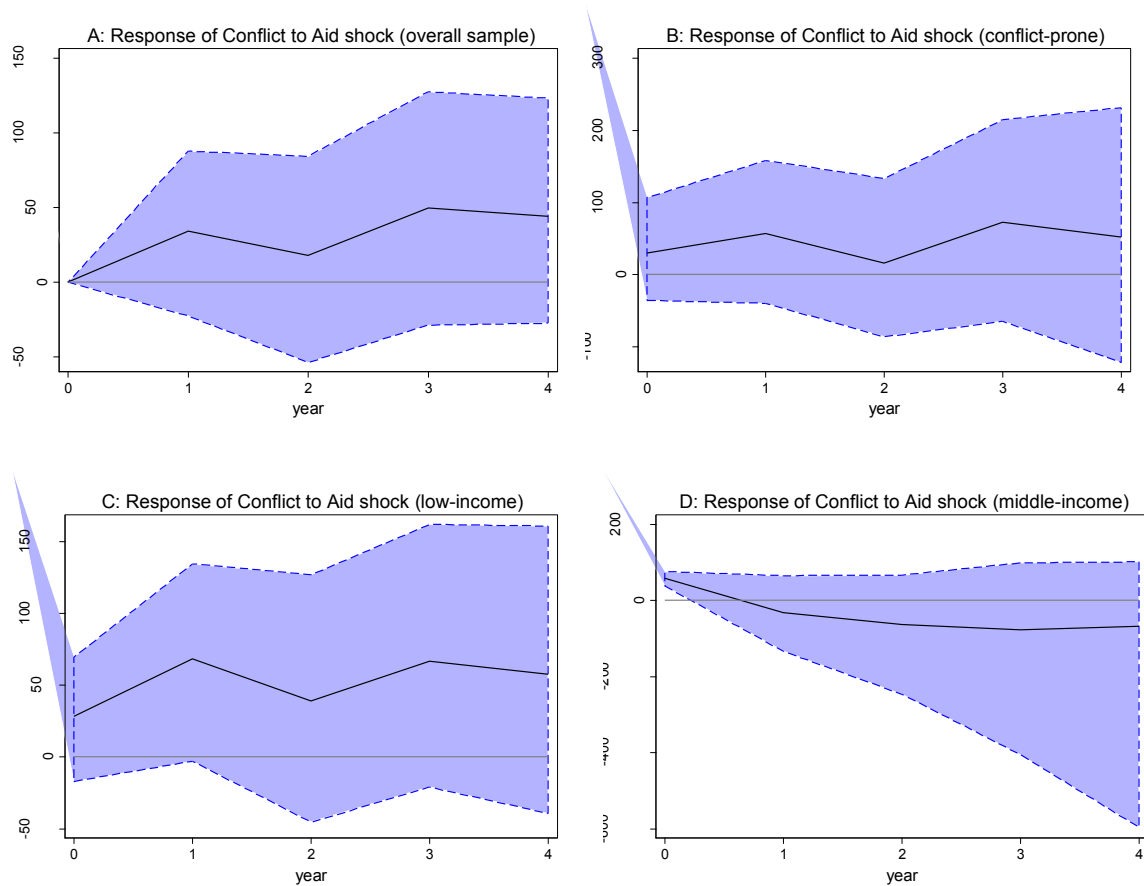


Fig.3. Impulse-response functions of conflict fatality to foreign aid. The different panels of the figure exhibit the IRFs across the overall sample, conflict-prone group, low-income group, and middle-income group. In each panel, the estimated average IRF is plotted by solid line, while the 95% confidence intervals generated through Monte Carlo simulations with 500 repetitions are plotted by broken lines.

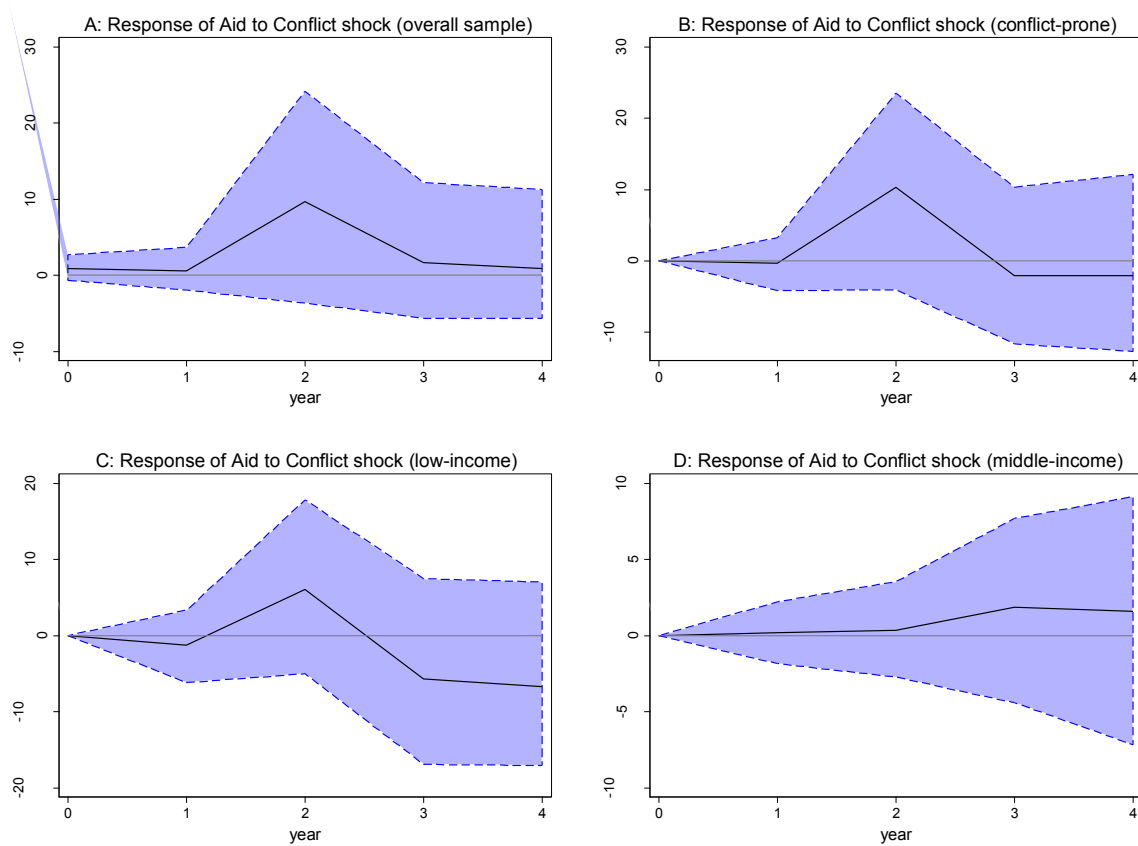


Fig.4. Impulse-response functions of foreign aid to conflict fatality. The different panels of the figure exhibit the IRFs across the overall sample, conflict-prone group, low-income group, and middle-income group. In each panel, the estimated average IRF is plotted by solid line, while the 95% confidence intervals generated through Monte Carlo simulations with 500 repetitions are plotted by broken lines.

On the other hand, how does foreign aid respond to the changes of conflict? The dynamic response of foreign aid to a one positive standard deviation shock in conflict fatality is depicted in Fig.4. As is shown in Panel A, given a conflict fatality shock (which corresponds to an increase of amount of battle-related deaths by 5), the aid per capita received by a typical developing country is not significant at any period except for the second year. One possible explanation for such lagged response pattern is that most of the aid agencies make the country-specific aid decision every other year. Even the intensification of a conflict is taken into consideration by the aid agencies; their bureaucratic characteristics make them go through many

steps to take an action (Easterly, 2002). At the second year, the amount of foreign aid per capita reaches the peak with the magnitude of \$10, which implies that the distribution of foreign aid is quite sensitive to the escalation of conflict. The next two panels express similar reactions of foreign aid to conflict shock for the conflict-prone group and the low-income group. Panel D displays the IRF for the middle-income group, exhibiting that the distribution of foreign aid among middle-income developing countries is not sensitive to the sharpen conflicts.

Fig.3 and Fig.4 together capture the dynamic relationships between foreign aid and conflicts. We find that income levels matter in such analysis. For the middle-income developing countries, although increasing foreign aid would lower conflict fatality, aid distribution is not sensitive to the degree of conflict. For the low-income and conflict-prone countries, aid delivery is responsive to the degree of conflict in a two-year lag, but the outcome of increasing foreign aid turns out to be disappointed.

#### **4.3 Dynamic Relationships (Aid and Development)**

In this part, we examine the dynamic feedback effects between foreign aid and development, while holding all other shocks equal to zero. From Fig.5 and Fig.6, we do not find any significant evidence supporting that foreign aid per capita is sensitive to the shock in infant mortality rate, but we note that foreign aid in the conflict-prone and low-income countries is lagged responsive to a one standard deviation shock in GDP per capita. Panel B and C of Fig.5 show significant negative effects of GDP shock on foreign aid for the conflict-prone and low-income developing countries. Coincidentally, the significant turning point of foreign aid happens at the second year after a GDP shock, which exhibits the same reaction pattern of foreign aid to conflict, as is shown in Fig.4. It is inferred from Fig.5 and Fig.6 that, aid agencies pay much attention to the conflict affected and poorer regions, instead of the richer developing countries. However, the

distribution of foreign aid relies heavily on the conditions of income development rather than non-income development. Moreover, there is large room for improving the reaction rate of foreign aid.

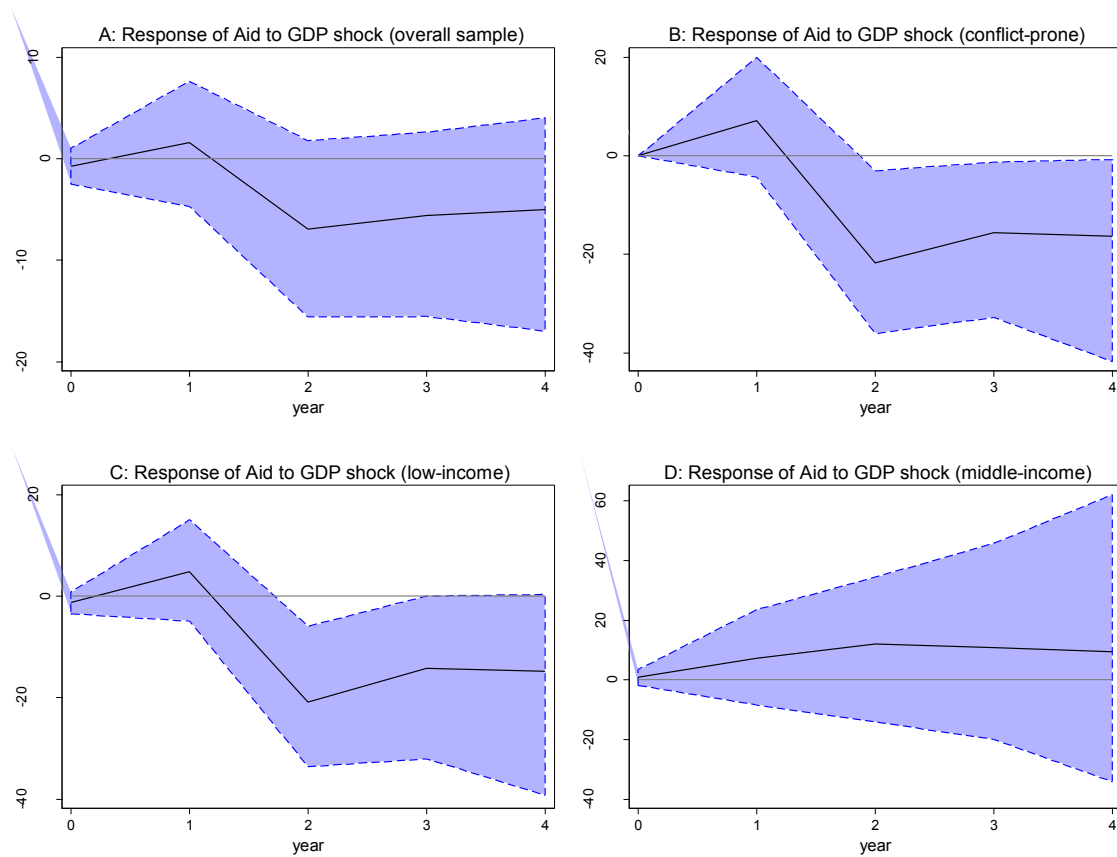


Fig.5. Impulse-response functions of foreign aid per capita to GDP per capita. The different panels of the figure exhibit the IRFs across the overall sample, conflict-prone group, low-income group, and middle-income group. In each panel, the estimated average IRF is plotted by solid line, while the 95% confidence intervals generated through Monte Carlo simulations with 500 repetitions are plotted by broken lines.

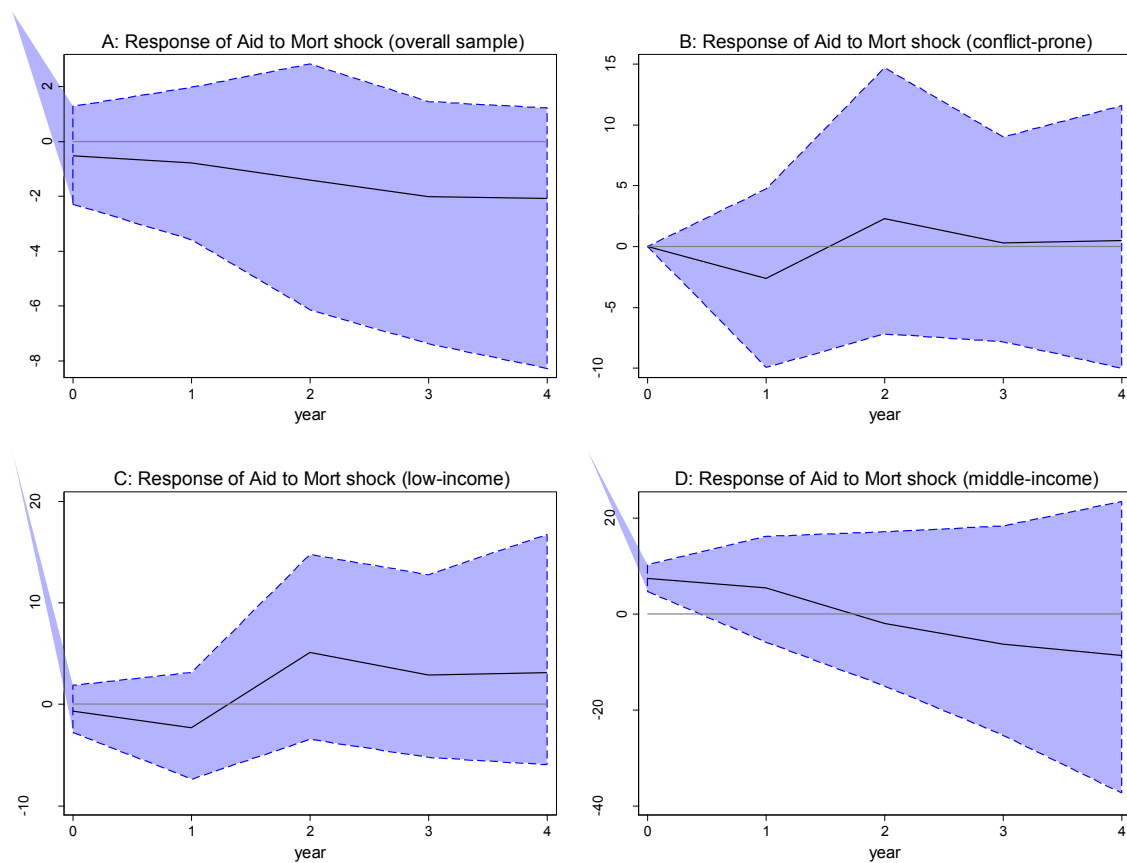


Fig.6. Impulse-response functions of foreign aid per capita to infant mortality rate. The different panels of the figure exhibit the IRFs across the overall sample, conflict-prone group, low-income group, and middle-income group. In each panel, the estimated average IRF is plotted by solid line, while the 95% confidence intervals generated through Monte Carlo simulations with 500 repetitions are plotted by broken lines.

Another well-discussed debate is that whether foreign aid really benefits the recipients in terms of development. The IRF results also contribute to this issue. Fig.7 tells that foreign aid shock to GDP is only positive for the low-income developing countries. Quantitatively, the amount of GDP per capita will be increased by \$9 with respect to an increase of foreign aid per capita by \$3.3. Also, Fig.8 shows that infant mortality rates in the conflict-prone and low-income groups negatively respond to the shock in foreign aid. Regarding the middle-income developing countries, the effects of aid on either GDP or infant mortality rate are not significant. Therefore,

an increase in foreign aid is showed to be very useful in enhancing the development of the poor and conflict-prone countries.

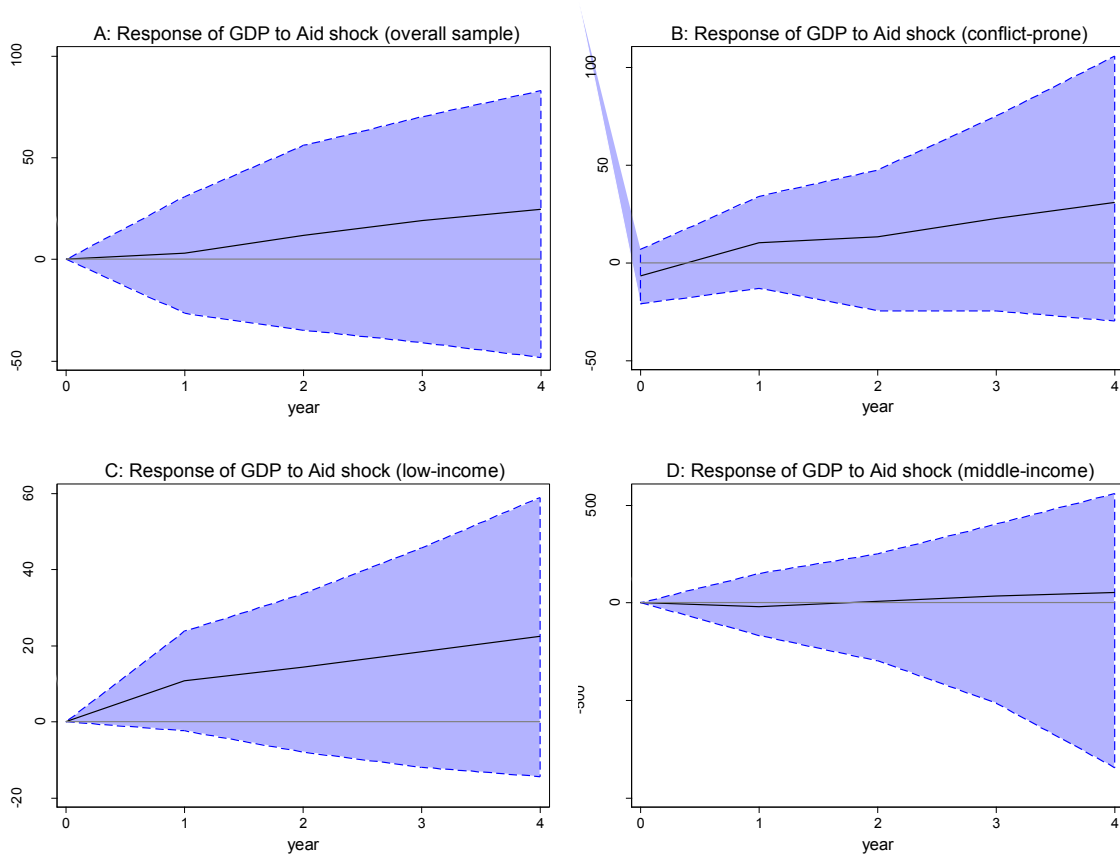


Fig.7. Impulse-response functions of GDP per capita to foreign aid per capita. The different panels of the figure exhibit the IRFs across the overall sample, conflict-prone group, low-income group, and middle-income group. In each panel, the estimated average IRF is plotted by solid line, while the 95% confidence intervals generated through Monte Carlo simulations with 500 repetitions are plotted by broken lines.



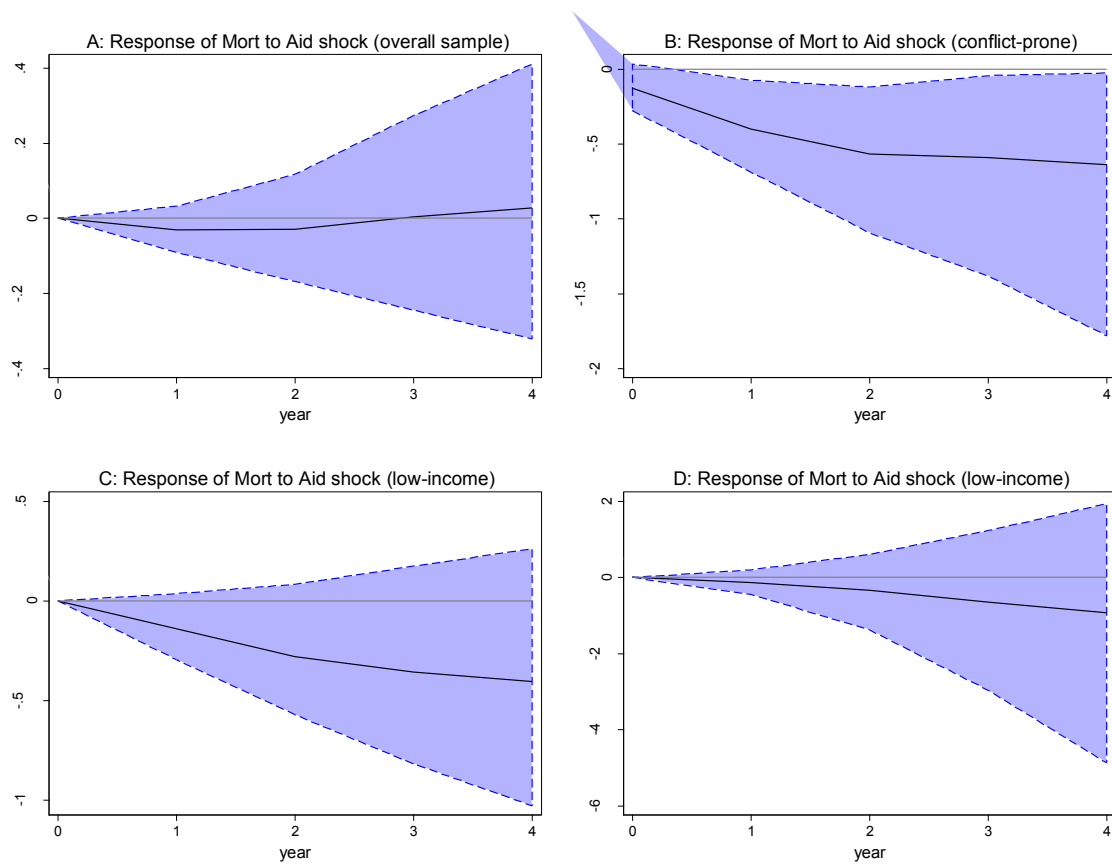


Fig.8. Impulse-response functions of infant mortality rate to foreign aid per capita. The different panels of the figure exhibit the IRFs across the overall sample, conflict-prone group, low-income group, and middle-income group. In each panel, the estimated average IRF is plotted by solid line, while the 95% confidence intervals generated through Monte Carlo simulations with 500 repetitions are plotted by broken lines.

## 5. Conclusion

The main purpose of this study is to illustrate how foreign aid interacts with the levels of development and conflict in dynamic patterns. By employing panel VAR model and directed acyclic graphs (DAGs), we are able to demonstrate how a shock (increase) to one variable results in the responding changes of another variable. It is aware that the dynamic interdependences among aid, development, and conflict are largely relied on the economic and political contexts. Thus, we also contribute to conducting our analysis condition on different wealth levels and

conflict proneness. More specifically, we divide the overall sample into three sub-clusters: low income countries, middle income countries, and conflict prone countries.

The most important findings of our study is that, foreign aid only appears to reduce conflict in middle income developing countries with relatively wealthier income level; but foreign aid performs well in enhancing the development of the poor and conflict-prone countries. In addition, we find that foreign aid is responsive to development or conflict shock in a two-year lag. The results of this study contribute to neo classical political thought as well as policy ramifications. We argue that foreign assistance policies of donors are reactive rather than proactive.

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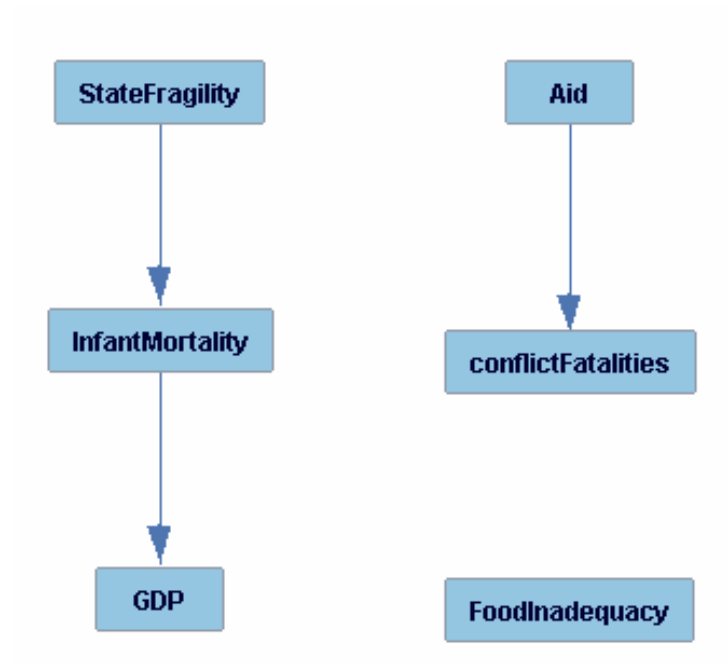
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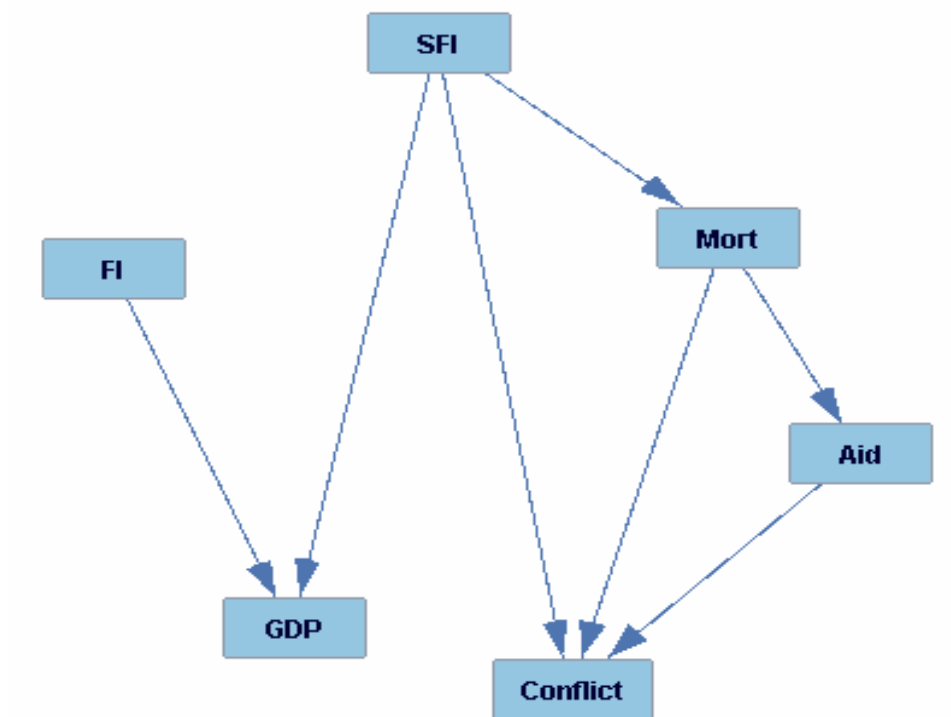
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## Appendix

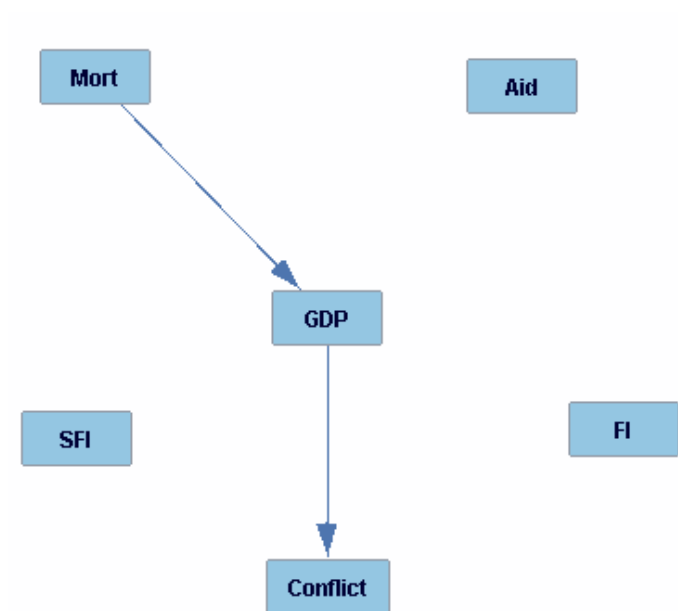
- Income less than 4000 (47 countries)



- Income between 4000 and 12500 (30 countries)

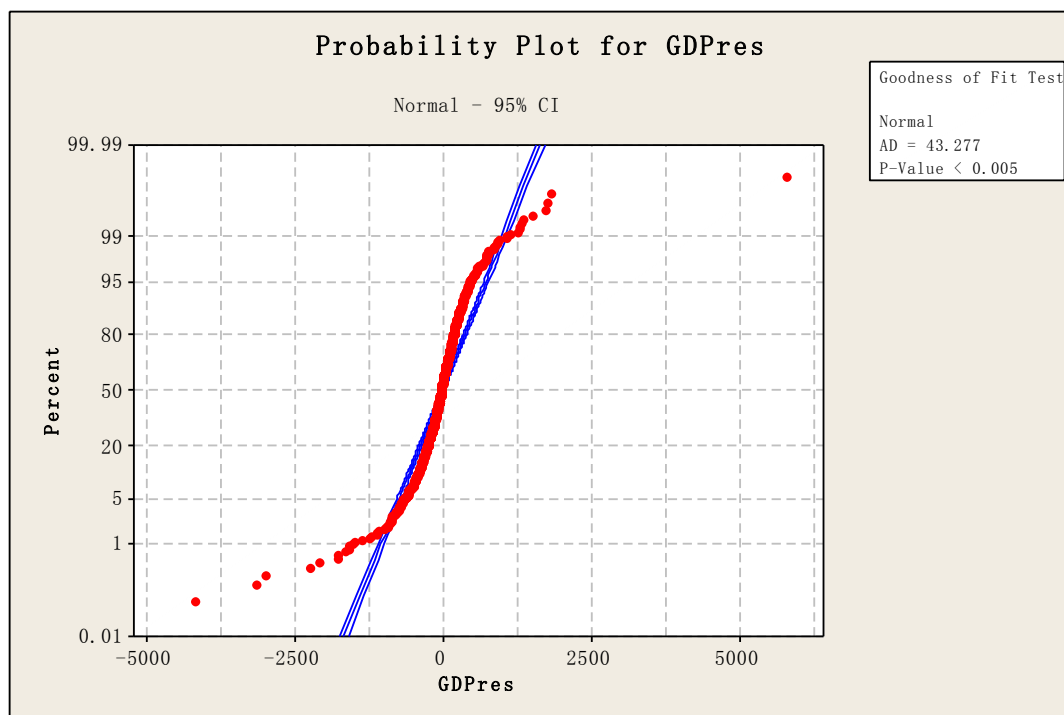


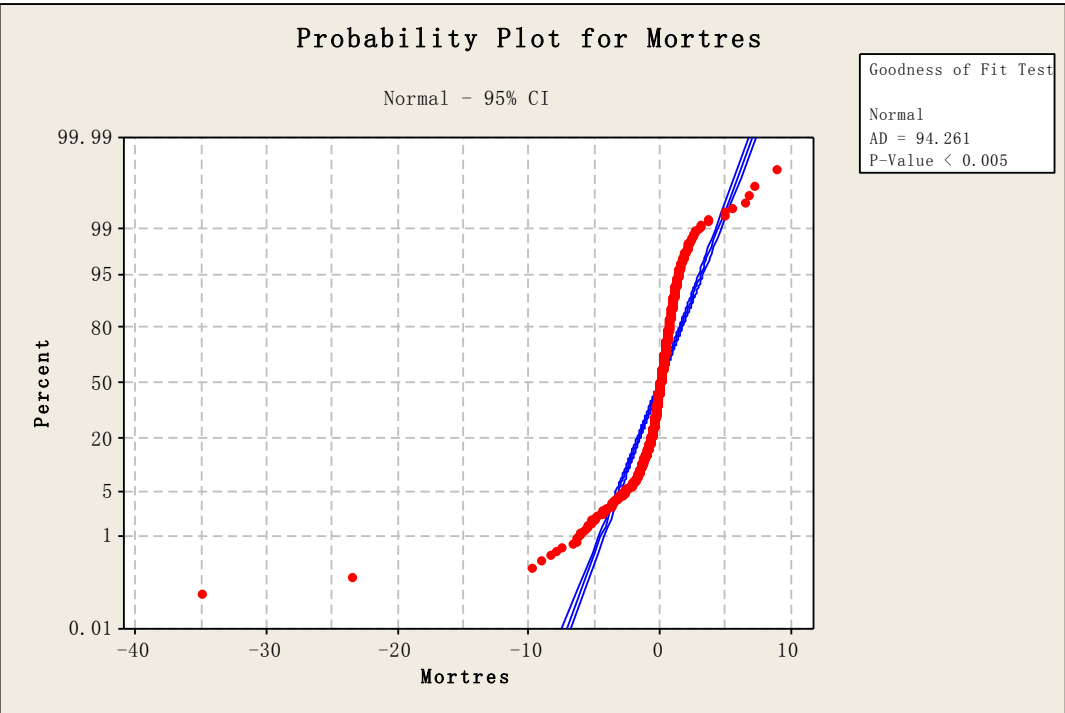
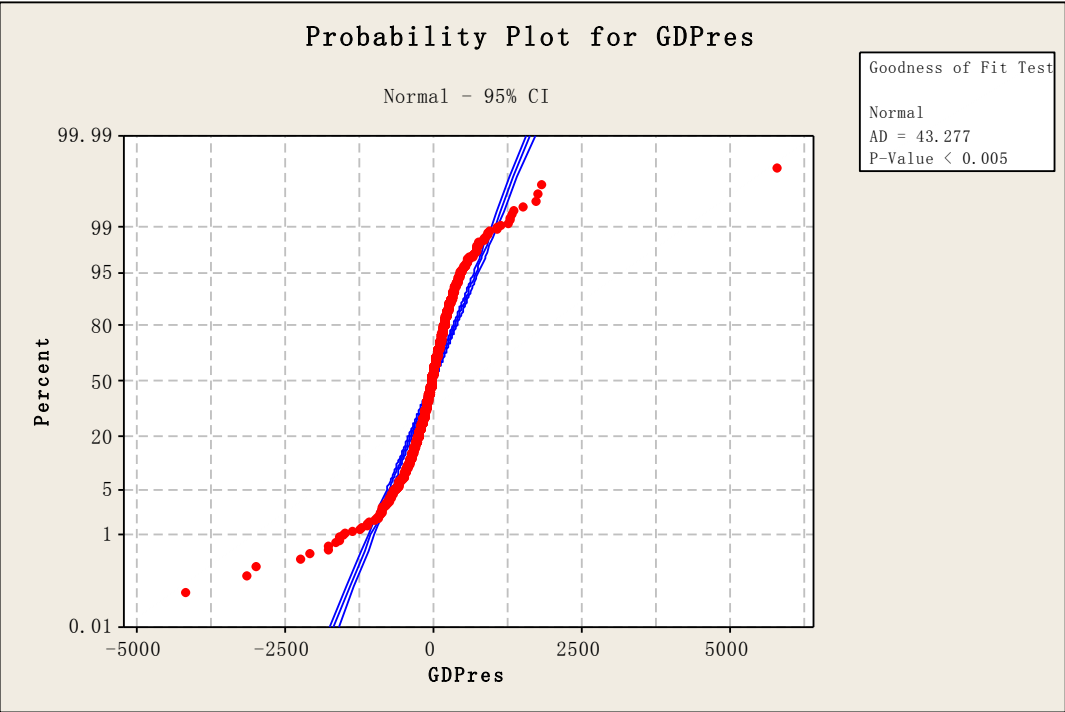
- Conflict-affected (29)



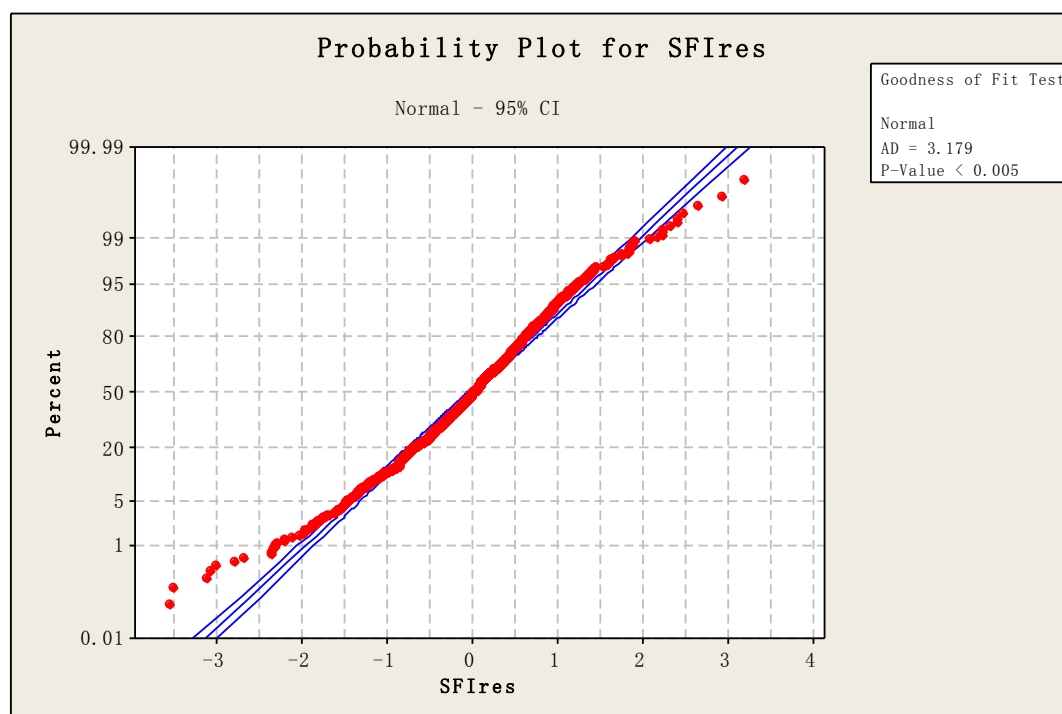
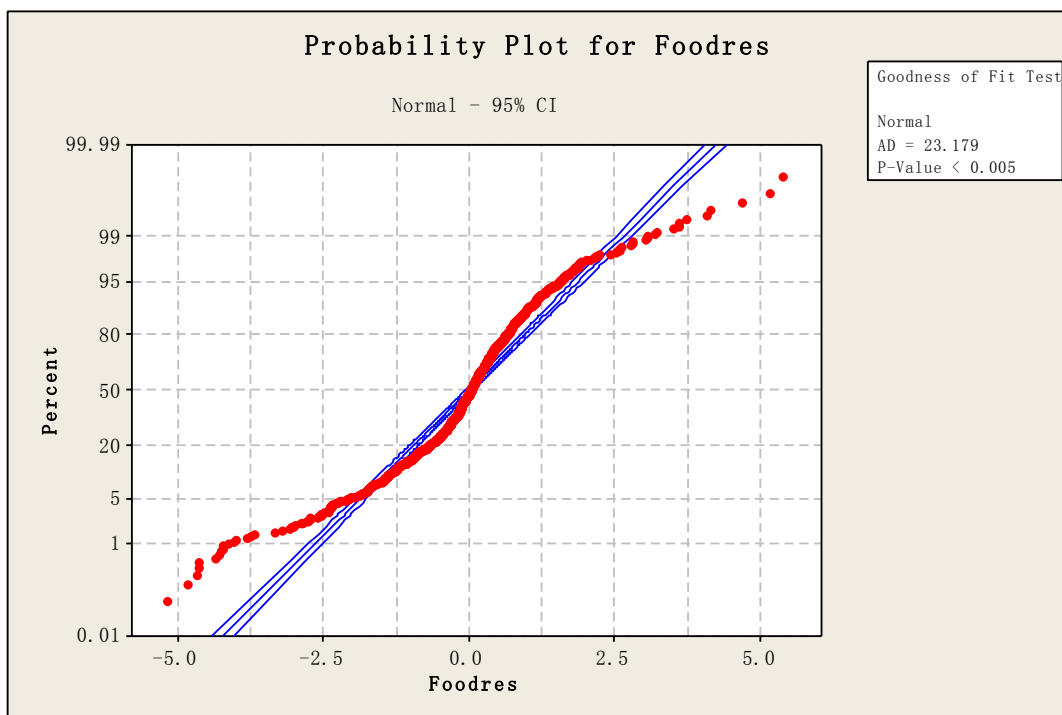
- **Non-Gaussian test results**

Normal probability plot and Anderson-Darling (AD) test (attached inside the probability plot figure) are presented for each variable. The probability plot includes percentile points for corresponding probabilities of an ordered data set. The middle line is the expected percentile from the distribution based on maximum likelihood parameter estimates. The left and right lines represent the lower and upper bounds for the confidence intervals of each percentile. The null hypothesis of AD test is that the data has a normal distribution.



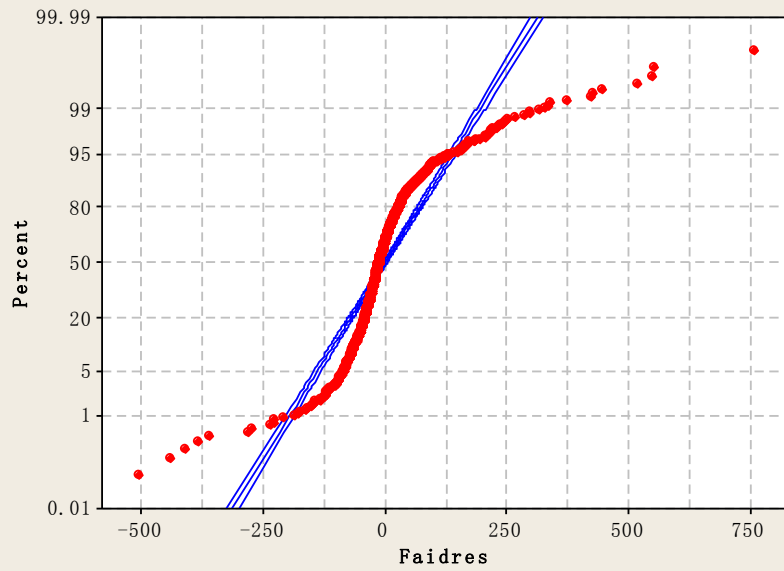






# Probability Plot for Faidres

Normal - 95% CI



Goodness of Fit Test

Normal  
AD = 66.870  
P-Value < 0.005